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Mental Health over the Life Course: Evidence for a U-Shape?*

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Abstract

We aim to identify the age-profile of mental health while introducing minimal bias to reach identification. Using mental health data from the US Panel Study of Income Dynamics (PSID) we apply first difference estimation to derive an unbiased estimate of the second derivative of the age effect as well as an estimate up to a linear period trend of the first derivative. Next, we use a battery of estimators with varying restrictions to approximate the first derivative. We find conclusive evidence that the age profile of mental health in the US is not U-shaped and tentative evidence that the age-profile follows an inverse U-shape where individuals experience a mental health high during their life course. Further analyses, using German and Dutch data, confirm that these results do not only apply to the US, but also to Germany and to the Netherlands.

Keywords: Mental Health, Age-period-chort
JEL Codes: I1, I18

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1 Introduction

Mental health problems are highly prevalent: approximately 20% of the working age population suffers from a mental disorder at any point in time and lifetime prevalence is estimated to be up to 50% (OECD, 2012). This high prevalence results both in an extremely large burden of disease (Murray et al., 2012; Whiteford et al., 2013), as well as significant societal costs: mental health problems are estimated to be the leading cause of years lived with disability worldwide (Whiteford et al., 2013) and the societal cost of mental disorders is estimated to be 3 to 4% of GDP in OECD countries (OECD, 2012, 2014). Therefore, it is important to know which groups are especially susceptible to mental health problems, so that interventions can be targeted at these groups.

One factor that appears to play a role in the burden of mental health problems is age. A number of studies have investigated the age-pattern of mental health (Bell, 2014; Blanchflower & Oswald, 2008, 2016; Le Bon & Le Bon, 2014; Lang, Llewellyn, Hubbard, Langa, & Melzer, 2011; Page, Milner, Morrell, & Taylor, 2013) and the majority of these studies have found that mental health follows a U-shaped pattern in age: young and old individuals generally experience better levels of mental health than individuals in, or close to, middle age (Blanchflower & Oswald, 2008, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011). These results suggest that society would do well to invest more resources targeted at care and prevention of mental health problems among the middle aged.

All except one of these studies reporting U-shapes use cross-sectional evidence (i.e., Blanchflower & Oswald, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011). However, investigating mental health trajectories over the life course is not without its caveats. By definition age, period and cohort are perfectly collinear (once an individual's age and the current year are known, it is possible to determine which year they were born). As a result, cross-sectional evidence of which age groups currently experience lower or higher mental health provides insufficient knowledge on the age-pattern of mental health, as it provides no evidence on whether the observed differences between age groups can be attributed to age effects or cohort effects. Hence, cross-sectional evidence cannot be generalized to future cohorts and age groups, and can provide no indication of whether interventions should either be targeted at specific cohorts or specific age groups.

Because of the fundamental collinearity between age, period and cohort effects, statistical analysis on the subject requires assumptions with various degrees of arbitrariness that cannot be tested. A number of approaches has been suggested to tackle the problem, especially in the related literature on the age-effects of well being and life satisfaction, all with different assumptions and (dis)advantages. Unfortunately, these different approaches often lead to conflicting results. For example, studies assuming cohort effects are negligible consistently report U-shapes in mental health, life satisfaction or well-being (Blanchflower & Oswald, 2016, 2017; Graham & Pozuelo, 2017; Laaksonen, 2018; Le Bon & Le Bon, 2014; Lang et al., 2011), whereas studies on well-being assuming that period effects are negligible consistently report no U-shapes (FitzRoy, Nolan, Steinhardt, & Ulph, 2014; Frijters & Beatton, 2012; Kassenboehmer & Haisken-DeNew, 2012). Since the nature of the Age, Period and Cohort (APC) problem prevents formal testing of many of these assumptions the true age-profile remains unknown.

An alternative approach, proposed by De Ree and Alessie (2011) and Van Landeghem (2012) and used by Cheng, Powdthavee, and Oswald (2017), stands out because of its lack of need for arbitrary assumptions. By focusing on the first differences of life-satisfaction or well-being[1], these studies can identify age effects up to a linear trend. Hence, while the methods employed in these studies cannot prove the existence of a U-shape in mental health as individuals age (since the linear trend remains unknown), they can provide proof when the U-shape is nonexistent. The studies using this method generally find evidence supporting a U-shaped relationship between well-being (Van Landeghem, 2012; Cheng et al., 2017) or life satisfaction (De Ree & Alessie, 2011) and age.

Nevertheless, the inability of these studies to identify the linear age-trend is troubling, as this means that the true age-profile still remains unkown. To address this issue, Cheng et al. (2017) improve on the method applied by De Ree and Alessie (2011) and Van Landeghem (2012). However, their method has certain identification problems (for a more detailed explanation, see Appendix A). Therefore, the current study applies the method proposed by De Ree and Alessie (2011) and Van Landeghem (2012), but aims to provide more information on the linear age-effect by also providing the results of a battery of estimations using varying cohort restrictions.

[1] Using this method they effectively estimate the second derivative with respect to age of a life-satisfaction/well-being equation.

We use data from three countries: the US Panel Study of Income Dynamics (PSID), as well as the German Socio-Economic Panel (SOEP) and the Dutch LISS panel. Our results indicate that the U-shape is not the dominant functional form in the relationship between mental health and age. In contrast, we find that the age-related profile of mental health likely follows an inverse U-shape, suggesting that the young and the elderly might be particularly at risk of developing mental health problems.

Aside from its relevance to mental healthcare and prevention policy, the methodological contribution of this paper to the literature is threefold. Firstly, to our knowledge, this paper is the first to apply the first difference approach proposed by De Ree and Alessie (2011) and Van Landeghem (2012) on mental health. As such, this study is the first to investigate the age-pattern of mental health without the necessity of arbitrary assumptions. Secondly, this paper introduces a relatively new approach regarding cohort restrictions. While it is not new to restrict a single cohort when using age, period and cohort effects as control variables, the current adaptation of the method - restricting only a single cohort when age effects are of primary interest and varying this cohort restriction across estimations - is new. Lastly, in contrast with a large fraction of the literature, this paper presents results from multiple estimation strategies for the linear age-effect. This is important, as different methodological choices appear to lead to different outcomes. Hence, just presenting one estimation strategy based on (a certain set of) arbitrary assumptions does not provide the complete picture.

This paper is structured as follows. Section 2 discusses the existing literature on the age-profile of mental health and well-being as well as the commonly applied methodologies. Section 3 provides a detailed explanation of the econometric methods used in this paper, after which Section 4 describes the data used for the main analysis. Results are provided in Section 5 and Section 6 contains the further analyses. Section 7 provides detailed discussion of the main result, after which section 8 provides a conclusion.

2 Background

Before delving into the literature on well-being, life satisfaction or mental health and age, it is important to understand the age-period-cohort (APC) problem and the proposed solutions to the problem. A much quoted (Bell & Jones, 2014, 2013, 2015) example of the distinction between age, period and cohort effects is the conversation between a senior worker (A) and a junior worker (B) from (Suzuki, 2012):

> A: I can't seem to shake off this tired feeling. Guess I'm just getting old. [Age effect]
>
> B: Do you think it's stress? Business is down this year, and you've let your fatigue build up. [Period effect]
>
> A: Maybe. What about you?
>
> B: Actually, I'm exhausted too! My body feels really heavy.
>
> A: You're kidding. You're still young. I could work all day long when I was your age.
>
> B: Oh, really?
>
> A: Yeah, young people these days are quick to whine. We were not like that. [Cohort effect] (Suzuki, 2012).

The problem is that every combination of two items of this list perfectly predicts the third. In other words, age, period and cohort effects together exhibit perfect collinearity. As a result, they cannot be estimated in a standard regression equation. Many methodological solutions have been proposed to solve this problem, each with its own caveats.

We will not only report literature regarding the age-profile of mental health, but also the age-profile of life-satisfaction and well-being. These three concepts are closely related, as individuals with low life-satisfaction or well-being are more likely to report lower mental health and vice versa and as such, these strands of literature have been intertwined. Furthermore, the combined literature on life-satisfaction and well-being has been more extensive than the literature that focused exclusively on mental health.

Perhaps the simplest method to circumvent the APC problem is by simply assuming that either period, or cohort effects are negligible and can thus be ignored. Multiple studies have assumed that cohort effects are irrelevant (Blanchflower & Oswald, 2016, 2017; Graham & Pozuelo, 2017; Laaksonen, 2018; Le Bon & Le Bon, 2014; Lang et al., 2011) and all of these studies report U-shaped age profiles of mental health, life satisfaction or well-being. Others have instead assumed that period effects are irrelevant, which makes it possible to estimate age effects using fixed effects approaches (FitzRoy et al., 2014; Frijters & Beatton, 2012; Kassenboehmer & Haisken-DeNew, 2012; Piper, 2015). Most of these studies argue that there is no U-shaped relation between age and life satisfaction (FitzRoy et al., 2014; Frijters & Beatton, 2012; Kassenboehmer & Haisken-DeNew, 2012). The exception is provided by

Piper (2015) whose results suggest that British individuals between 16 and 30 have a lower life satisfaction as they age.

Another method, which requires slightly weaker assumptions, is to assume that age, period and cohort effects are all relevant, but that either age groups, periods or cohorts close together have equal coefficients. E.g., using this assumption, one can run a regression using single-year age dummies, single-year period dummies, but five- or ten-year cohort dummies. Some studies have followed this approach (Blanchflower & Oswald, 2008; Lin, Hwang, & Deng, 2015; Page et al., 2013), but their results are mixed. Both Page et al. (2013) and Lin et al. (2015) provide no conclusive evidence regarding a U-shape in suicide rates and subjective wellbeing, respectively. Blanchflower and Oswald (2008) find evidence of a U-shape in well-being and rates of depression and anxiety.

Others have used Hierarchical APC (HAPC) models, which require the assumption that cohort and period effects are completely random (Yang, 2008; Bell, 2014; Beja, 2017). Yang (2008) and Bell (2014) use HAPC models and find no evidence of a U-shape in happiness and mental health, respectively. Beja (2017) applies a HAPC model to world wide life satisfaction data and does find a U-shaped relationship between age and life satisfaction for individuals aged 15-69.

The use of parameter restrictions has often been criticized (Bell & Jones, 2013, 2014; Luo & Hodges, 2016; De Ree & Alessie, 2011; O'Brien, 2017). By relying on arbitrary assumptions to reach identification, all of the studies above are likely to suffer from biases of unknown size. For example, by assuming cohort effects are negligible estimated age-effects include cohort-effects as well as age-effects.

To circumvent this issue, several authors/studies have attempted to identify age-effects using only minimal assumptions by focusing on the second derivative of the age profile (Cheng et al., 2017; De Ree & Alessie, 2011; Van Landeghem, 2012). The analyses in these studies can identify age patterns up to a linear trend; they can identify the second derivative of the age profile, but not the first.

This means that the true age-pattern remains unknown. For example, the second derivative of age might indicate the existence of a U-shape, but if the first derivative is sufficiently large (small), mental health, life statisfaction, or wellbeing is nevertheless continuously increasing (decreasing) over the life course. In such a case, a statistically significant second derivative only means that there is significant curvature in the downward (upward) sloping age-trend. Hence, while the methods employed in these studies cannot prove the existence of a U-shape in mental health as individuals age (since the linear trend remains unknown), they can prove that the U-shape is nonexistent.

The studies using this method generally find evidence supporting a U-shaped relationship between well-being (Van Landeghem, 2012; Cheng et al., 2017) or life satisfaction (De Ree & Alessie, 2011) and age. However, these results require caution as the exact functional form remains unknown.

Cheng et al. (2017) claim that they can identify the linear trend in age (i.e. the first derivative), by using a two-stage procedure where they first regress an equation for the first differences in life-satisfaction using only a set of year dummies as independent variables. They then use the residuals from this first regression as the dependent variable in the second stage regression that included a coefficient for age and a constant.

However, their analysis suffers from three problems. Firstly, it implicitly assumes that time trends are not linear. Consequently, in the presence of a linear time trend, their estimate of the first derivative cannot capture the linear time and age trend in the second stage as they have already been filtered out in the first stage. Secondly, since the first stage estimation ensures that the sum of the dependent variable in the second stage equals zero, the constant in the second stage is rather a product of the data structure than an estimator of the linear age-effect. Hence, the method applied by Cheng et al. (2017) cannot provide any additional information to the methods proposed by De Ree and Alessie (2011) and Van Landeghem (2012). Third, their coefficients are likely to be biased due to the fact that the variables for age and year are likely to be correlated, which they implicitly assume is not the case by running separate regressions for the two. For a more detailed explanation, see Appendix A.

What this overview of the literature teaches us is that there is no panacea when it comes to APC estimation. Any method for identifying APC effects either has a large probability of misspecification (parameter restrictions) or is underidentified (only inferring information about the second derivative). As a result, different methods can lead to different outcomes. This is clearly illustrated when studies assuming cohort effects are negligible are compared to studies assuming instead that period effects are negligible. The first category of studies consistently reported U-shapes, while the latter consistently reported no U-shapes. As a result, there is no consensus on the exact age-profile of mental health, life satisfaction and well-being.

With regard to mental health specifically, four of the six papers cited here do find a U-shaped age profiles of mental health variables (Blanchflower & Oswald, 2008, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011). The fifth study (Page et al., 2013) provides no clear evidence in favour of or against the existence of a U-shape. However, this study only investigates the rather extreme case of suicide and is not necessarily focused on the existence of a U-shape.

The only study cited here that explicitly reports no U-shaped age profile in mental health uses the HAPC model (Bell, 2014). Bell (2014) argues that previous findings of a U-shape are the result from confounding of cohort effects and that, instead, mental health declines as individuals age.

In the sections that follow we investigate the age-profile of mental health using US panel data. To ensure that our results are not the artefacts of methodological choices, we will first estimate the second derivative using first differences, after which we will attempt to approximate the first derivative using a battery of parameter restrictions. Both methods will be explained in more detail below. Our results indicate that there is no U-shape in the relationship between mental health and age. In contrast, the relationship might even consist of an inverse U-shape.

3 Method

3.1 Second derivative

We base our analysis on Van Landeghem (2012) and De Ree and Alessie (2011) who both show that identification of the second derivative can be obtained by taking first differences from the dependent variable and regressing them on age as well as a set of year dummies[2]. I.e., assume our Data Generating Process (DGP) is given by:

$$MH_{i,t} = \beta_0 + \beta_1 age_{i,t} + \beta_2 age_{i,t}^2 + \tau year_t + \gamma_t + \sum_{\phi=1905}^{C} \alpha_\phi cohort_i(\phi) + \epsilon_{i,t}, \tag{1}$$

[2]Van Landeghem (2012) uses unaltered year dummies, De Ree and Alessie (2011) use Deaton Paxson year dummies (Deaton & Paxson, 1994). Both methods give equivalent estimates for the second derivative in our case.

where $MH_{i,t}$ denotes the mental health score of individual i in year t, $age_{i,t}$ denotes the age of individuals i in year t, τ is the parameter denoting a linear period effect and γ_t denotes the deviation from the linear period effect, $cohort_i(\phi)$ denotes a set of cohort dummies taking value one if ϕ equals the birth year of individual i and zero otherwise and $\epsilon_{i,t}$ denotes the error term. The parameters β_1 and β_2 are the parameters of interest, since they determine whether mental health is U-shaped over the life-course. By first differencing (1), and using the fact that $age_{i,t}^2 - age_{i,t-1}^2 = 2age_{i,t} - 1$, this can be rewritten as:

$$\Delta MH_{i,t} = (\beta_1 - \beta_2 + \tau) + (\gamma_t - \gamma_{t-1}) + 2\beta_2 age_{i,t} + \tilde{\epsilon}_{i,t}, \tag{2}$$

where $\tilde{\epsilon}_{i,t} = \epsilon_{i,t} - \epsilon_{i,t-1}$. Hence, we can identify β_2 by using first differences of the mental health scores as dependent variables in a regression analysis with age multiplied by two and a set of year dummies as independent variables. We can only identify β_1 with this method if we are willing to make an assumption about the linear period trend τ.

3.2 First derivative

We will use parameter restrictions on cohorts to approximate the first derivative with respect to age. The least restrictive parameter restrictions model that allows for both linear age- and year-effects as well as nonlinear cohort-effects, but is still identified, is one where only two out of all cohorts are expected to have equal coefficients. This model is still biased, but the bias is minimized to the difference between the two cohort effects that are assumed to be equal. Additionally, if the average cohort effect approximates zero, on average our estimation of the linear age-effect should be close to the true coefficient.

Therefore, we estimate models of mental health using OLS with cluster robust standard errors with a continuous age variable, age squared, a set of year dummies and a set of (restricted) cohort dummies as independent variables. To reach identification the period dummies start from the second available year (i.e. 2001 is the reference year) and the cohort dummies consist of a full set of cohort dummies minus a reference cohort (1902)[3] and with the restriction that one cohort has a coefficient equal to the cohort from the previous birth year. [4]

[3] grouping all cohorts with year of birth <1910 leads to similar results

[4] We do not use cohort restrictions on cohorts born before 1920 and after 1993, since these cohorts contain too few individuals (less than 100) to provide accurate results.

4 Data

We use data from the Panel Study of Income Dynamics (PSID) for the main analysis. The PSID started in 1968 and consists of a nationally representative sample of individuals living in families. From 2001 onwards, with the exception of 2005, the family interviews contained 6 questions belonging the abbreviated Kessler psychological distress scale (K-6) which were asked to the head and/or the partner of head of the household. The K-6 is a broad screener that can be used to assess non-sepcific psychological distress and the prevalence of serious mental illness in the general population (Kessler et al., 2002, 2010) and has been well validated (Prochaska, Sung, Max, Shi, & Ong, 2012; Furukawa et al., 2008; Furukawa, Kessler, Slade, & Andrews, 2003; Gill, Butterworth, Rodgers, & Mackinnon, 2007). We will use this variable as a measure of mental health. The family interviews were held biennially. Hence, in this study we use data from 9 family interviews, as 2017 data is not yet available and the 2005 interview did not contain the K-6 questions.

The K-6 consists of 6 questions asking how often individuals felt certain negative emotions during the last 30 days (sadness, nervous, restless, hopeless, that everything was an effort, worthless) which they can answer on a scale from 1 (all of the time) to 5 (none of the time) (Kessler et al., 2002). Generally these scores are inverted later so that a score of 0 means 'none of the time' and a score of 4 means 'all of the time' after which the scores from the different questions can be summed into a single score. For convenience, we linearly transformed this single score so that it ranges from 0 to 100, where 0 indicates that an individual answered 'all of the time' to all 6 questions and a score of 100 indicates that an individuals answered 'none of the time' to all 6 questions.[5]

In our sample for analysis we included only the direct respondents of the family interview, as they were the ones answering the K-6 questions. Summary statistics of our final sample can be found in Table 1.[6] Our first difference approach requires the presence of at least two consecutive observations of the K-6 for each individual in our set. As a result we lose 3,237 out of 14,378 individuals. However, there is almost no variation between both samples in terms of age, year of birth and K-6 score. Detailed summary statistics of this second sample

[5] Using the untransformed data does not alter the results.

[6] When split by gender the summary statistics show no substantial differences between men and women, see Tables 3 and 4 in Appendix B.1.

Table 1: Population summary statistics

	N	Mean	Standard deviation	Minimum	Maximum
Age	14,378	38.7	15.99	16	99
Year of Birth	14,378	1965.84	18.10	1902	1997
Year	14,378	2005.08	4.92	2001	2015
Gender					
Female	7,867	54.72%			
Male	6,511	45.28%			
K-6 score (0-100)	14,378	83.93	17.27	0	100

Summary statistic at first observation (baseline) for each individual

can be found in Table 5 in Appendix B.1. Hence, we do not expect this to influence our results.

Figures 1, 2 and 3 provide a graphical analysis of the relation between mental health and age, period and cohort. In the graph, all years are pooled together and age-specific average K6 scores are stratified by 10-year cohort.[7] It is interesting to note that our mental health measure does not show a strong U-pattern and that this is the case for both men and women. Mental health appears to increase at every age until individuals are around 70, after which - at least for women - it declines slightly.

Another interesting observation is that visible cohort or period effects appear to be small: values for equal age groups of different cohorts are generally very similar. While this provides no conclusive evidence, it suggests that the patterns that we do see in the graphs might be due to age-effects.

5 Results

5.1 Second derivative

To ensure that our estimates are robust to autocorrelation we have used cluster robust standard errors. Additionally, to reduce any effects of over- or undersampling in the PSID we performed our estimations with PSID family sample weights. Table 6 provides the results of the estimation of equation (2). It is interesting to note that our estimation results for

[7] Age groups within each cohort that consisted of less than 100 individuals were left out of the graph as the small samples resulted in volatile K6 scores for those age groups.

Figure 1: Average scores for: K6 (0-100 scale)

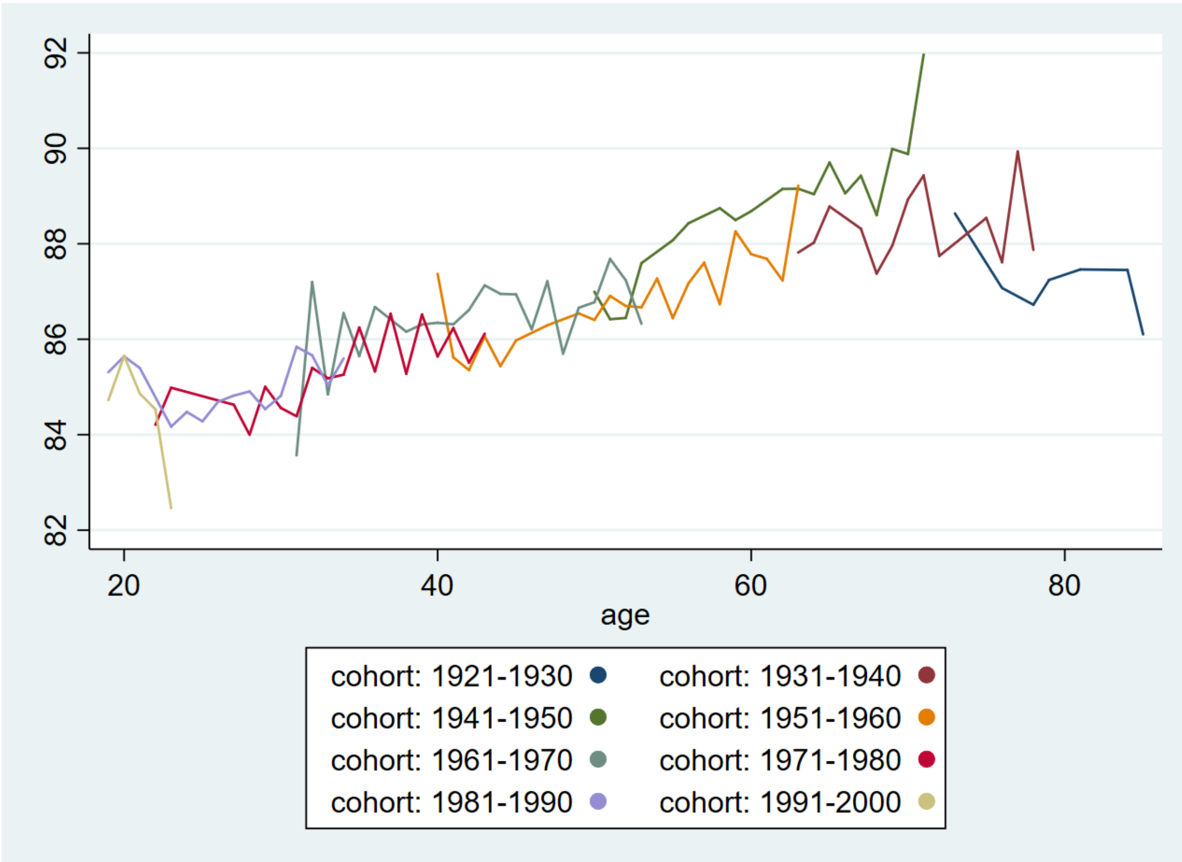


Figure 2: Scores women: K6 (0-100 scale)

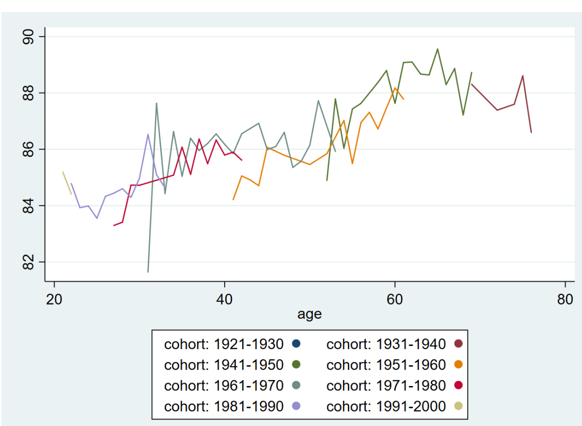


Figure 3: Scores men: K6 (0-100 scale)

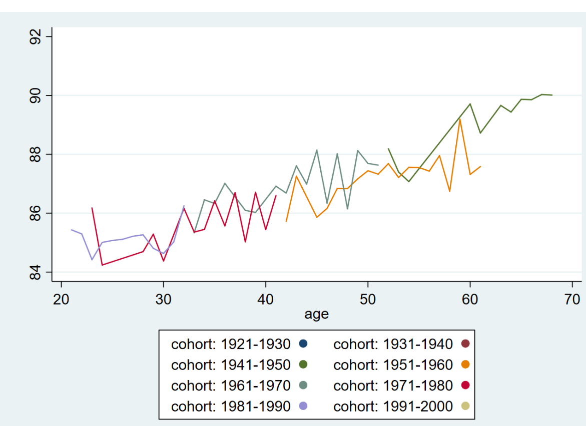


Table 2: Estimation results: second derivative

Δ K6 (0-100)	Full sample	Women	Men
$2age_{i,t}$	-0.009***	-0.009***	-0.009***
	(0.002)	(0.003)	(0.003)
Constant	1.203***	1.545***	0.734
	(0.313)	(0.408)	(0.489)
Clustered SE	YES	YES	YES
Observations	37,292	23,142	14,150
Number of ID	11,141	6,737	4,404

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

β_2 do not vary across genders, both have a statistically significant estimate of -0.009. This indicates that there is no U-shape in mental health over the life course.

On the contrary, our estimation results for the second derivative with respect to age (β_2) indicate that there might be an inverse U-shape in mental health over age. However, whether this inverse U-shape truly exists depends on the linear term, which is not identified. If we are, however, willing to assume that there exists no linear time trend ($\tau = 0$), women's mental health would be continuously increasing until they reach old age (they reach their peak mental health at age 83), whereas men would experience a more profound inverse U-shape: given our current estimate, mental health would peak at age 39. Regardless of the size of the linear age effect, our finding of a negative second derivative disproves the existence of a U-shaped age profile in mental health.

5.2 First derivative

Figures 4-6 provide the estimated coefficients for the linear age effect for different cohort restrictions. For each restricted year of birth, the coefficient of that cohort is restricted to be equal to the coefficient of the previous cohort. I.e., if the restricted cohort is the one born in 1921, then the coefficient for the cohort effect of 1921 is assumed to be equal to that of 1920.

The parameter restrictions result in estimations of the linear age effect that vary between 0.412 and 0.673. Given these two extremes mental health would either peak somewhere between age 44 (linear age effect is 0.412) and age 72 (linear age effect is 0.673).

Figure 4: Estimates for linear age effect

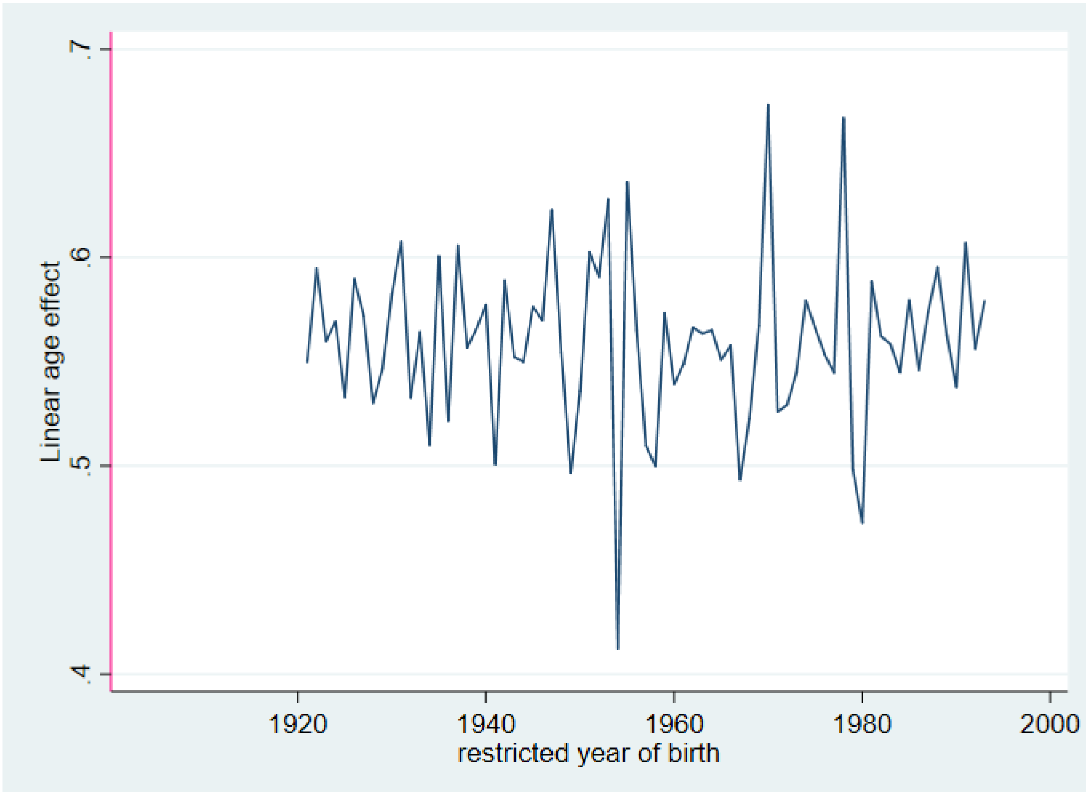


Figure 5: Linear age effect: women

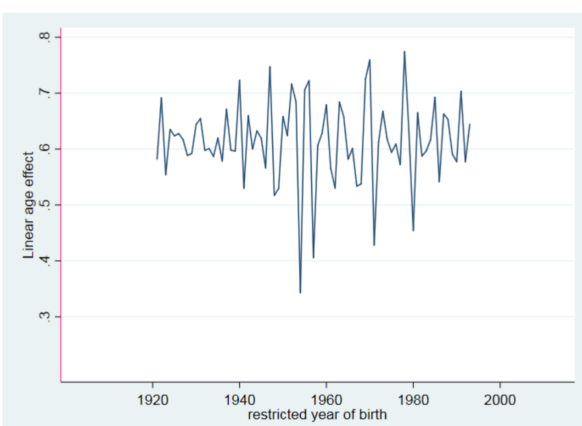
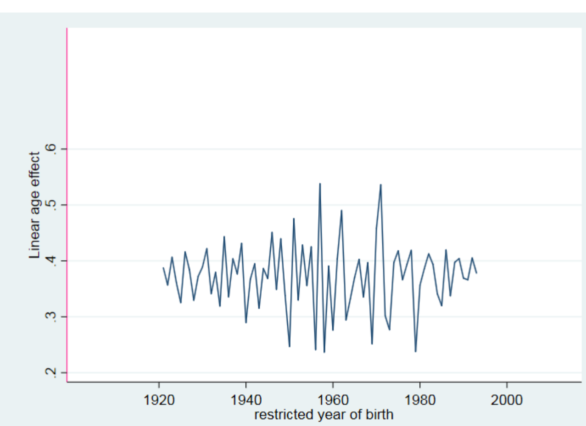


Figure 6: Linear age effect: men



When we stratify by gender, we find that the estimated linear age effects for women generally tend to be much higher than the linear age effects for men, suggesting that women reach their peak mental health later in life. For men, estimated linear age effects range from 0.237 to 0.538, suggesting mental health peaks sometime between age 25 and age 58. For women, the estimated coefficients vary between 0.343 and 0.774, suggesting that their mental health peaks sometime between age 37 and age 84. Apparently, the estimated ages at which individuals reach peak mental health using the varying cohort restrictions approach do not differ substantially from the estimated ages using the second derivative approach with the assumption of no linear period trend.

Consequently, if we are willing to assume that the bias caused by the parameter restrictions is either negligible, or at least close to zero on average, we can conclude that mental health is inversely U-shaped over the life course. This result applies to both men and women.

6 Further Analysis

6.1 Functional form

It could be that the DGP in this study is too restrictive. After all, in this study, as well as in the literature, there is no clear theoretical foundation for the assumption that mental health should either be linear or (inversely) U-shaped over age. Perhaps the age-profile of mental health is more complicated and, therefore, not approximated by the assumed DGP. It is relatively easy to test this hypothesis by assuming a less restrictive DGP. Following Van Landeghem (2012), we estimate equation (2) using a set of dummies for age instead of a single continuous age variable. The age-dependent second derivative is then given by differencing the coefficients of the age dummies. If the initial second order polynomial assumption is correct, the estimated age-dependent second derivative should only exhibit minimal variation around a straight line. If instead the pattern of the age-dependent second derivative is more complicated, this would suggest that our initial assumed DGP is incorrect.

A plot of the age-dependent second order derivatives is given in appendix B.2. As the graph clearly shows, the age-dependent derivative only shows minimal variation around a straight line. Additionally, a Ramsey RESET test (Ramsey, 1969) of equation (2) to assess the null hypothesis for no misspecification provides p-values of 0.035, 0.290 and 0.222 for the entire sample, women and men, respectively. While the small p-value for the entire sample might suggest that the analysis suffers from some form of misspecification, the large p-values of the separate specifications for men and women suggest that this might largely be due to gender differences. Hence, the choice of a second order polynomial for age in equation (1) does not appear to cause misspecification. Consequently, the conclusions that the age-profile of mental health is not U-shaped and that it might even follow an inverse U-shape appear to be valid.

6.2 Attrition

There might be a possibility that individuals of certain ages with certain mental health levels are more likely to drop out of the sample. E.g., it might be that older individuals with more mental health problems have lower survival rates than older individuals with less mental health problems. If this is the case our estimate of the second derivative would be biased. However, when we add a dummy variable for attrition (indicating whether an individual will have left the panel in the next wave) to our second derivative estimation our results remain relatively unchanged (see Appendix B.3). Additionally, the coefficient for the attrition dummy is statistically insignificant ($p > 0.10$). Similarly, when we perform the second derivative estimation including only those individuals that were present in all waves, we find an estimate for the second derivative that is slightly higher, but still negative and statistically significantly different from zero ($p < 0.05$) and not statistically significantly different from our previous estimations ($p > 0.10$) (see Appendix B.3). Consequently, our results appear to be relatively unaffected by panel attrition.

6.3 Period and cohort trend

So far, we have provided two estimation strategies for the linear age-effect. The first estimation strategy (using first differences) required the assumption of a negligible period trend in order to identify the age-effect. The second strategy (using varying cohort restrictions) required the assumption of a negligible cohort trend. The degree of certainty about the first derivative hinges on the credibility of these assumptions. In other words, is there reason to believe either a linear period or cohort trend is more or less likely? In Appendix B.6 we provide two graphs: the first provides average K-6 (0-100) scores per year of observation and the second provides average K-6 (0-100) scores per cohort. Note that both provide no conclusive evidence on the linear trend, as the averages are biased with age effects, and period or cohort effects. Nevertheless, average K-6 (0-100) scores show strikingly little variation over time, suggesting that perhaps the assumption of no linear period trend might not be too unrealistic.

6.4 Multiple Countries

Our finding that mental health is inversely U-shaped over the life course runs counter to the current literature, which more often than not reports a U-shape in mental health, wellbeing or life satisfaction. It might be though that this is simply due to the fact that we focus on the US, which might be the exception to the U-shaped rule (Blanchflower & Oswald, 2009). To test this assumption, we reperform our analysis of the second derivative on data from the Netherlands and Germany.

For our analysis of the Netherlans, we use data from the Dutch LISS panel [8] , which consists of a representative sample of the Dutch population. The LISS panel contains data on individual mental health for the years 2007-2017, with the exception of 2014. Mental health is measured using the abbreviated 5-question version of the Mental Health Inventory (MHI-5) (Ware Jr & Sherbourne, 1992), which is a widely used and well validated instrument, specifically for mood and anxiety disorders (Veit & Ware, 1983; Rumpf, Meyer, Hapke, & John, 2001; McCabe, Thomas, Brazier, & Coleman, 1996). The MHI-5 can be summarized in a score ranging from 0 to 100, where higher scores indicate better mental health.

For Germany we use data from the German Socio-Economic Panel (SOEP). The SOEP is a long-run panel with data on German households from 1984 to 2016. A large number of papers have used SOEP to investigate a U-shape in life-satisfaction and well-being (e.g., Kassenboehmer & Haisken-DeNew, 2012; Frijters & Beatton, 2012; Van Landeghem, 2012; Baetschmann, 2014; FitzRoy et al., 2014; Cheng et al., 2017; Rohrer, Brümmer, Schupp, & Wagner, 2018; De Ree & Alessie, 2011), but, to our knowledge, currently no study has used SOEP to investigate the age-profile of mental health.

[8] The LISS panel is a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register. Households that could not otherwise participate are provided with a computer and Internet connection. A longitudinal survey is fielded in the panel every year, covering a large variety of domains including work, education, income, housing, time use, political views, values and personality.

For mental health we use the Mental Component Summary scale (MCS), which is computed from answers to the SF-12v2 questionnaire using factor analysis (Andersen, Mühlbacher, Nübling, Schupp, & Wagner, 2007). The MCS is calibrated such that the population average is close to 50 and the standard deviation is close to 10, with higher scores implying better mental health. The MCS is available from 2002 onwards, hence we use data from all even years between 2002 and 2016, which resulted in data from 8 different years[9]

Estimated second derivatives for both datasets can be found in Table 7 of Appendix B.4. For Germany we find relatively similar results to the US, indicating that the non-existence of the U-shape in mental health in the US is not an isolated case. For the Netherlands we find a statistically insignificant second order derivative of 0.001 (SE: 0.002), indicating that either the second derivative is relatively close to 0 or our current assumed DGP might be misspecified for the Netherlands. We can test this last possibility in the same way as we did previously. Results for the age-dependent second derivative for the Netherlands can be found in Figure 8 of Appendix B.4. No clear age pattern emerges when looking at the age-dependent second derivative for the Netherlands, suggesting that the second derivative might indeed be close to zero. Additionally, a Ramsey RESET test (Ramsey, 1969) could not reject the null hypothesis of no misspecification with a p-value of 0.174. Consequently, the U-shape in mental health is not only absent when using US data, but also when using German and Dutch data.

7 Discussion

Our results consistently indicate that there is no U-shape in mental health over age, and that this finding is not limited to just the US. This is not in line with the literature, which frequently reports a U-shape (Blanchflower & Oswald, 2008, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011), which raises the question why our results differ.

One possible reason for the difference in results is that two of the four studies (Blanchflower & Oswald, 2016; Le Bon & Le Bon, 2014) use some form of mental healthcare use as proxies for mental health. The underlying assumption is that if the age profile of mental healthcare use consists of an inverse U-shape, the age profile of mental health must also be U-shaped. However, mental healthcare use might not be an adequate proxy for mental health and the

[9] 2002;2004;2006;2008;2010;2012;2014;2016

reliability of healthcare use as a proxy might be dependent on age (Clement et al., 2015; Alonso et al., 2007; Wang et al., 2005). This could bias the results.

Additionally, three of the four studies do not control for cohort effects, assuming that these are zero (Blanchflower & Oswald, 2016; Le Bon & Le Bon, 2014; Lang et al., 2011). However, this might not be the case, leading to biased results. Even when cohort effects are taken into account (Blanchflower & Oswald, 2008), all four studies use superfluous parameter restrictions, suggesting that cohort effects are perhaps not adequately controlled for (Bell & Jones, 2013).

Lastly, many of these studies used control variables other than cohort and period variables to estimate the age effects of mental health (e.g. Blanchflower and Oswald (2008) and Lang et al. (2011), and to some extent Blanchflower and Oswald (2016)). This is not problematic per se, but it does beg the question what is being estimated exactly. It is easy to imagine that most of the age effect of mental health is not a direct result of individuals becoming older, but of other factors, physically and in society, that change as individuals age. In that sense adding control variables may seem like a good idea, but there is a vast number of factors that change as individuals age that potentially also affect mental health and it is difficult to asses in an analysis whether all relevant factors have been identified. As a result, when just a few of these factors are included in the analysis as control variables, it is unclear what the residual age effect found by the analysis consists of and, hence, it is difficult to interpret. Therefore, through the use of control variables, Blanchflower and Oswald (2008) and Lang et al. (2011) measure something fundamentally different (a residual age effect) from the crude age effect investigated in this study, which might lead to different results.

Indeed, when we perform an anlysis similar to Blanchflower and Oswald (2008), using 10-year cohort dummies and a variety of control variables we do find a U-shape in mental health, albeit a highly statistically insignificant one (see Appendix B.5). The combination of the two methodological differences (inadequate cohort controls and analysing a residual age-effect) force our previously negative, unbiased estimate for the second derivative to suddenly become positive. There is no clear interpretation that we can provide of this positive estimate, since it is unclear what it entails exactly as it combines both a cohort bias and an unknown residual age-effect. [10]

[10] When we add these same control variables to the second derivative approach used in this paper, we still consistently find a negative second derivative, although it is no longer significant at a 5% or 1% level (results

Moreover, our results are in line with the results of Bell (2014) if we are willing to assume that there is no linear period effect. Bell (2014) implicitly makes this assumption by using a HAPC model, and just as in this study finds a negative coefficient for the second derivative.

In this study we have used a very narrow definition of mental health. The WHO (2014) has defined mental health as 'a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community.' While the questionnaires used in this study capture some of this definition of mental health, they certainly do not encompass all of the definition by the WHO (2014). Specifically, the K-6 focuses more on the presence or absence of psychological distress than the holistic view of mental health proposed by the WHO (2014). On the other hand, non-specific psychological distress is a common symptom in a broad range of mental disorders (Kessler et al., 2002) and all three instruments used in this study have evidence suggesting they can function as valid screening tools in the general population (Gill et al., 2007; Rumpf et al., 2001). Hence, while the current study might not necessarily reflect mental health in its entirety, it does capture important aspects of mental health.

Knowing the crude age pattern of mental health (or psychological distress) is highly important, as it indicates which age groups are at risk for mental health problems. A logical further step then is to see which variables drive this age pattern, so that perhaps specific policies and interventions can be targeted at improving the mental health of at-risk groups. To identify suspect variables, future studies could investigate which variables correlate with the age pattern of mental health, after which researchers can focus on identifying causality. Both of these steps are outside the scope of the current study.

From our background section we conclude that there is no panacea when it comes to APC estimation. Any method for identifying APC effects either has a large probability of misspecification or is underidentified. As a result, while we can derive an unbiased estimate for the second derivative, when estimating the first derivative different methods will lead to different biases and different outcomes. Consequently, any study reporting results from an APC analysis should be interpreted with caution. We have tried to circumvent this problem by widely varying the restrictions on cohorts used to reach identification and also reporting

available upon request). However, it should be noted that these control variables could introduce significant endogeneity bias into the estimate (Glenn, 2009).

the results of an estimation where the linear period-effect is assumed to be zero, assuming that if all these different restrictions give similar results our results are less likely to be the artefact of methodological choices. However, it is almost impossible to know in what direction results from different restrictions might be biased since that requires knowledge on all elements of the APC-problem which are by definition unidentifiable. As a result, we cannot know with certainty that the methods applied in this study do not suffer from biases as a result of a linear period or cohort trend. The only certainty we can provide is that various estimates with different restrictions are at least less likely to all suffer from a similar bias than a study employing just a single set of restrictions.

In other words, while we cannot be completely certain that the true linear age-effect lies within the bounds reported by this study, we have tried to reduce this uncertainty. Moreover, we can be certain that our estimate of the second derivative is unbiased. Hence, we can say with certainty that there is no U-shape in mental health over age and that this study provides tentative evidence that mental health follows an inverse U-shape over the life course.

8 Conclusion

This study investigated how mental health changes over the life-cycle by first employing an unbiased estimator for the second derivative of the age pattern, after which the linear age-effect was estimated by widely varying the restrictions on cohorts to reach identification. While a decent body of literature suggests that the age-profile of mental health might be U-shaped, we find evidence that this U-shape does not exist and might in fact be a methodological artefact. On the contrary, our results suggest that the relationship between mental health and age might actually be closer to an inverse U-shape, where individuals experience a mental health high at some point during their lives. This finding is highly societally relevant as it suggests that the young and the elderly might be particularly at risk for mental health problems. Future research should investigate what the determinants of the age pattern of mental health are.

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Appendix

A Review of the method applied by Cheng, Powdthavee and Oswald (2017)

Cheng et al. (2017) investigate the age pattern of life satisfaction by examining a first difference equation with change-in-life-satisfaction as the dependent variable. To circumvent the problem of only being able to estimate the age-effect up to a linear trend, Cheng et al. (2017) state the following:

> We circumvent it by using a simple two-step approach. In the first stage, we estimate a regression equation for change-in-life-satisfaction in which the only independent variables are a set of time dummies. Next, we calculate the residual from that equation; this residual is a measure of what might be called the de-trended change in life satisfaction for every person in the data set. We then use the residual as the dependent variable in the change-in-life-satisfaction regression equation. (Cheng et al., 2017)

Furthermore, in their appendix Cheng et al. (2017) provide the following assumed Data Generating Process (DGP) for the change-in-life-satisfaction equation with controls:

$$LS_{it} - LS_{it-1} = \Delta LS_{it} = \beta_0 + \beta_1 A_{it} + \theta PC_{it} + \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \lambda T_t + \epsilon_{it}, \tag{3}$$

> where i and t index individual and time; LS_{it} is overall life satisfaction; A_{it} is individual's age; PC_{it} represents panel conditions or the length of time the individual is present in the panel at time t; $\boldsymbol{X}'_{it}$ is a vector of standard socio-economic variables *[...]*; T_t is time trend; and ϵ_{it} is the error term. (Cheng et al., 2017)

Since PC_{it} and $\boldsymbol{X}_{it}$ are part of the further analysis and are not an aspect of the main analysis, we will assume $\theta = 0$ and $\boldsymbol{\gamma} = \mathbf{0}$. However, loosening these assumptions does not substantially alter the conclusions below.

Suppose there are four years of observations for $LS_{i,t}$ (i.e., $t = 1, ..., 4$), this would imply that there will be three years of observations for the first differences in equation (3) (i.e. $t = 2, 3, 4$). A regression with $\Delta LS_{i,t}$ as the dependent variable and a full set of year dummies as the independent variables would estimate the following:

$$\Delta LS_{i,2} = p_2 + u_{i,2},$$
$$\Delta LS_{i,3} = p_3 + u_{i,3},$$
$$\Delta LS_{i,4} = p_4 + u_{i,4}, \tag{4}$$

where p_t is a year-specific constant and $u_{i,t}$ is the error term to be used as dependent variable in the second stage. Assuming momentarily that age and year are uncorrelated, it is easy to see that, given equation (3), $p_t = \beta_0 + \lambda t$. In other words, including a full set of year dummies filters the linear age trend (β_0, the constant in the first-difference equation) out of the residuals ($u_{i,t}$) in the first stage and, therefore, it can never be identified in the second stage.

Even if we misinterpreted the two-way procedure and, in fact, one year-dummy was excluded from the set of equations (4) the linear age-effect would still be filtered out of all estimations of $u_{i,t}$ where there was a year dummy, and the estimations of $u_{i,t}$ without the year dummy would also include the linear period-effect next to the linear age-effect. Hence, even then, the linear age-effect cannot be identified in the second stage.

Additionally, by assuming β_0 denotes the linear age-effect of life satisfaction, Cheng et al. (2017) implicitly assume that there is no linear time-effect in the original life-satisfaction equation, since such a linear time-effect would result in a constant in the change-in-life-satisfaction equation given by equation (3). Such a linear time-trend would indeed be captured by p_t, but as explained above, so would the linear age-effect.

One might wonder what the estimated constants assumed to represent the linear age-effect in Cheng et al. (2017) consist of, if the method proposed by Cheng et al. (2017) cannot identify the linear age-effect. These constants are likely a product of the data structure and the estimated lows in midlife life-satisfaction are likely to equal the average age of all observations in the dataset. This is a result from the fact that age has not been centered, but the dependent variable (the estimated residuals from equation (4)) is.

More specifically, since the first-stage estimation contains a constant (a full set of year dummies captures the constant), we know that:

$$\sum_{j=1}^{n} \hat{u}_n = 0, \tag{5}$$

where n is the total number of observations in the set and $\hat{u}_n$ is the estimated residual from the first stage for every observation in the set. In the second stage Cheng et al. (2017) estimate the following regression model:

$$\hat{u}_n = \hat{\beta}_0 + \hat{\beta}_1 A_n + e_n. \tag{6}$$

Combining equation (5) and (6) yields

$$\sum_{j=1}^{n} \hat{u}_n = \sum_{j=1}^{n} (\hat{\beta}_0 + \hat{\beta}_1 A_n + e_n) = 0. \tag{7}$$

Since equation (6) also contains a constant $\sum_{j=1}^{n} e_n = 0$, hence we can derive that

$$\hat{\beta}_0 = -\hat{\beta}_1 \frac{\sum_{j=1}^{n} A_n}{n}. \tag{8}$$

The point at which equation (6) intersects with the X-axis is then given by

$$x = \frac{\sum_{j=1}^{n} A_n}{n}, \tag{9}$$

i.e., the average age in the set. Hence, the fact that Cheng et al. (2017) consistently find a negative constant is to be expected given their estimation method. The fact that they find a minimum for life-satisfaction at middle age is also to be expected, since the average observation of age in the set is likely to be in, or close to, middle-age.

B Graphs and Figures

B.1 Summary statistics

Table 3: Summary statistics: women

	N	Mean	Standard deviation	Minimum	Maximum
Age	7,867	38.08	15.99	16	97
Year of Birth	7,867	1965.91	18.19	1903	1997
Year	7,867	2004.55	4.73	2001	2015
K-6 score (0-100)	7,867	83.18	17.39	0	100

Summary statistic at first observation (baseline) for each individual

Table 4: Summary statistics: men

	N	Mean	Standard deviation	Minimum	Maximum
Age	6,511	39.38	15.97	16	99
Year of Birth	6,511	1965.76	18.00	1902	1997
Year	6,511	2005.72	5.07	2001	2015
K-6 score (0-100)	6,511	84.84	17.08	0	100

Summary statistic at first observation (baseline) for each individual

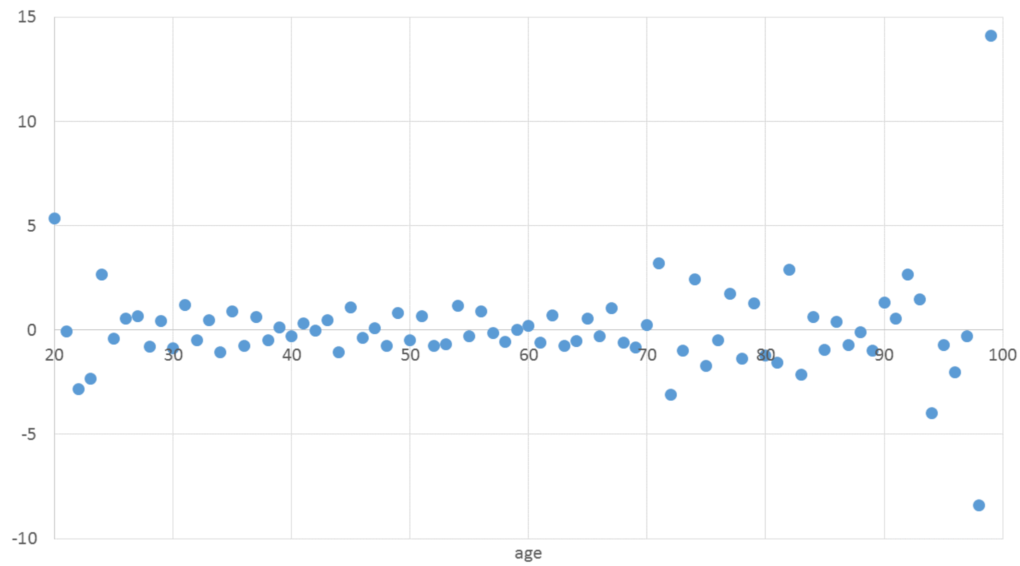
Table 5: Population summary statistics: individuals with at least two consecutive scores

	N	Mean	Standard deviation	Minimum	Maximum
Age	11,141	38.14	15.50	16	95
Year of Birth	11,141	1965.18	17.52	1905	1995
Year	11,141	2003.90	4.08	2001	2013
Gender					
Female	6,737	60.47%			
Male	4,404	39.53%			
K-6 score (0-100)	11,141	84.53	16.69	0	100

Summary statistic at first observation (baseline) for each individual

B.2 Age-dependent second derivative

Figure 7: Age-dependent second derivative



B.3 Attrition

Table 6: Estimation results: second derivative

Δ K6 (0-100)	Full sample	Individuals present in all waves
$2age_{i,t}$	-0.009***	-0.007**
	(0.002)	(0.003)
Constant	1.411***	1.231***
	(0.538)	(0.426)
Attrition_{t+1}	-0.217	
	(0.443)	
Clustered SE	YES	YES
Observations	37,292	19,130
Number of ID	11,141	3,826

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

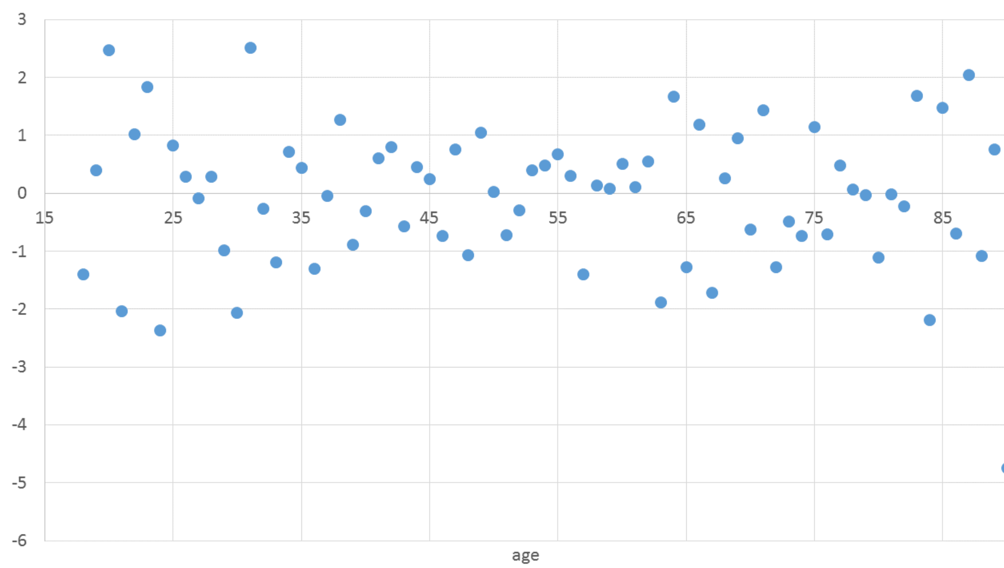
B.4 Netherlands and Germany

Table 7: Estimation results: second derivative

	Netherlands	Germany
$2age_{i,t}$	0.001	-0.006***
	(0.002)	(0.001)
Constant	0.373	0.793***
	(0.267)	(0.137)
Clustered SE	YES	YES
Sample weights		YES
Observations	33,511	111,706
Number of ID	9,250	35,286

Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 8: Age-dependent second derivative: Netherlands



Second derivative estimates for individuals aged >90 are not shown due to extreme outliers as a result of limited sample sizes for these age groups.

B.5 Residual age-effect with 10-year cohorts

Table 8: Estimation results: residual age-effect with 10-year cohorts

K6 (0-100)	
$age_{i,t}$	0.007
	(0.096)
$age^2_{i,t}$	0.001
	(0.001)
Cohort dummies	10-year
Year dummies	1-year
Controls	YES
Clustered SE	YES
Sample weights	YES
Observations	40,808
Number of ID	11,695

Control variables consisted of state dummies, the natural log of income, marital status dummies, education level dummies, employment status dummies, race dummies and a dummy variable denoting whether the household included children under 18.
Cluster robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B.6 Cohort and period trends

Figure 9: Average K6 scores per year (0-100)

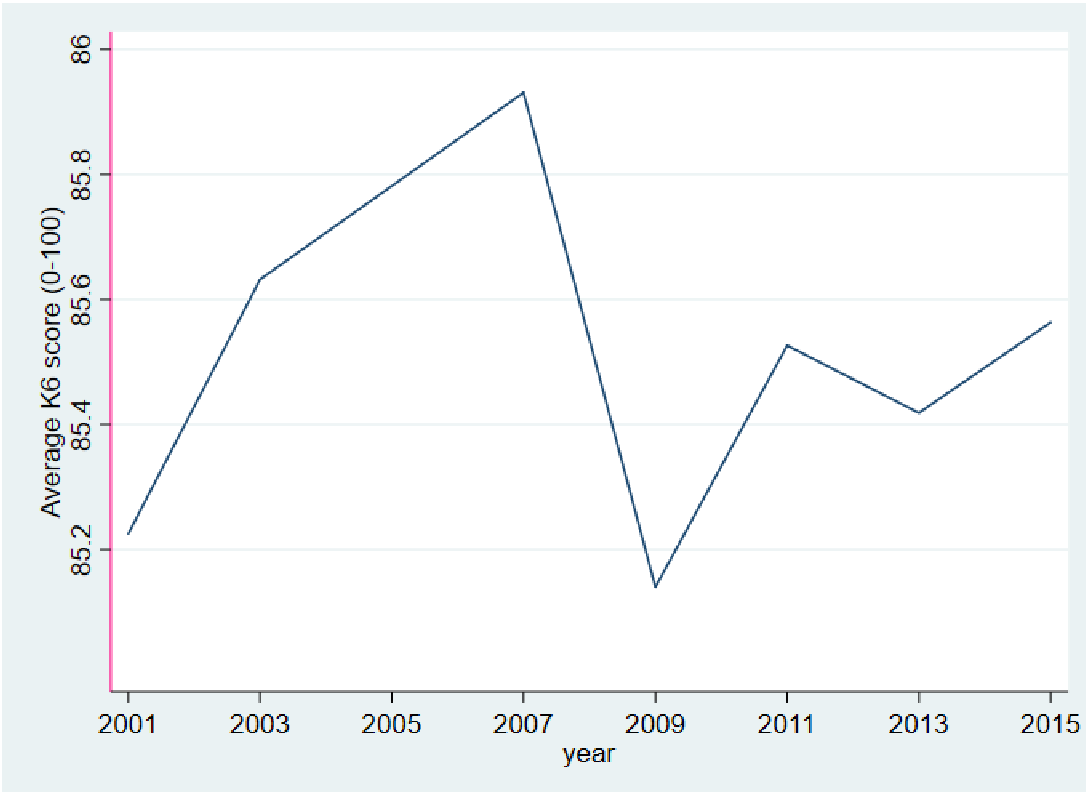
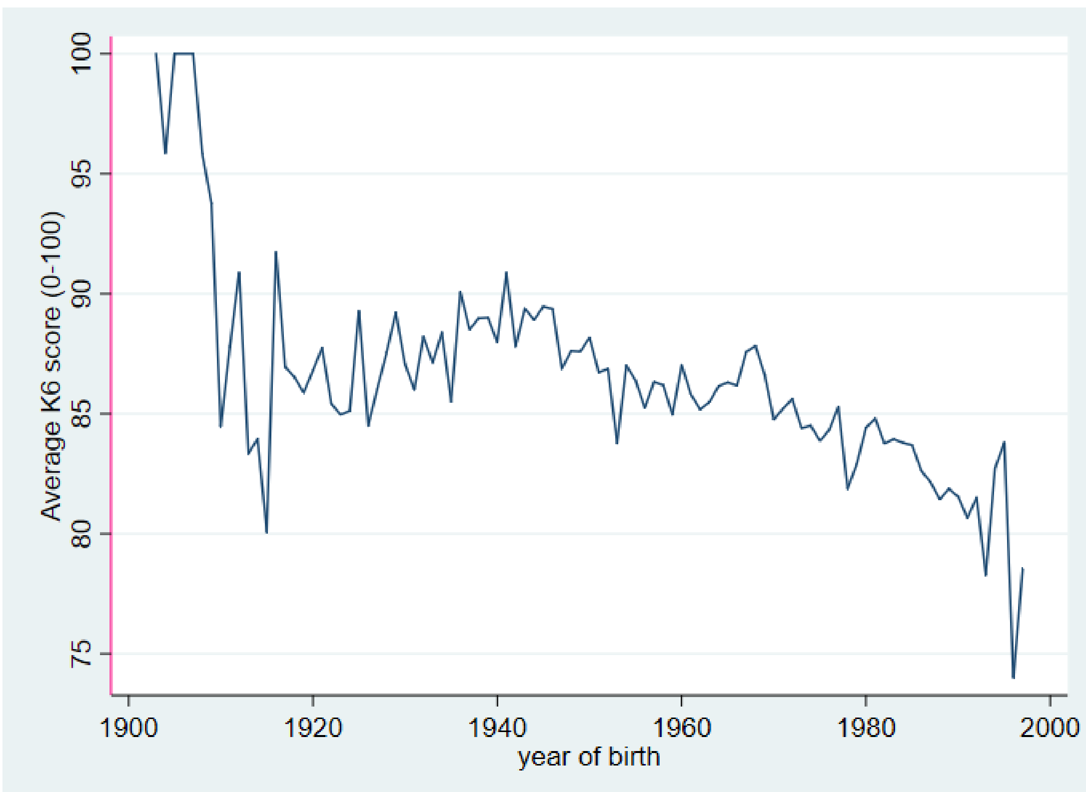


Figure 10: Average K6 scores per cohort (0-100)



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